Does the nudge effect persist? Evidence from a fi eld experiment using social comparison message in China

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Does the nudge effect persist? Evidence from a field experiment using social comparison message in China *

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Abstract

We designed and carried out a field experiment in which we imposed social comparison incentives and technical recommendations on student dormitories through electricity consumption reports and energy-saving suggestions materials, respectively. Our findings are as follows: 1) Regression results on all users show that the effect of social norms is not statistically significant. 2) A social comparison message has a heterogeneous effect on consumers' energy use. Low and high

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energy users reduced their electricity consumption by 26% and 14%, respectively, in the first week after the treatment. 3) The effect of social norms is time sensitive.

JEL: C93; D10; Q41

Keywords: Social norms; Social comparison message; Energy saving behavior

1 Introduction

Household energy consumption is one of the largest contributors to greenhouse gas emissions among human activities (Jones and Kammen, 2011). A U.S. Environmental Protection Agency (EPA) report found that the harmful gas generated from both commercial and noncommercial use of electricity is more than a quarter of the total harmful gas emissions (EPA, 2011). Economists and policy makers in energy sectors have focused on how pricing and subsidies can affect energy consumption. However, a Pigovian carbon tax or carbon emissions trading is politically not feasible in countries such as the United States. In addition, measuring the effectiveness of an energy efficiency subsidy requires knowledge of the demand elasticity of energy-efficient durable products. Without these parameters, there are deficiencies with subsidy-based programs. Moreover, a subsidy is also a depletion of limited public funds (Allcott, 2011).

Non-price interventions can be more cost effective in reducing consumers' energy consumption. Allcott (2011) evaluates a series of programs run by a private company called OPOWER which sends neighbors comparison reports on home energy consumption. Using a randomized natural field experiment with more than 600,000 treatments and control households across the United States, Allcott finds the average program reduces household energy consumption by 2%, which is equivalent to a short-run price increase of 11% to 20%. In addition, he finds a heterogeneous effect among high-end users and low-end users. Households in the highest decile of pretreatment consumption reduce energy consumption by 6.3%, while households in the lowest decile of pretreatment consumption reduce consumption by only 0.3%. Social norms have also been proved to be effective in other areas, such as recycling (Schultz, 1999), towel reuse (Goldstein et al., 2008), water consumption (Ferraro and

Price, 2011), voting (Gerber and Rogers, 2009), retirement saving (Beshears et al., 2009), and charity giving (Frey and Meier, 2004). See Farrow et al. (2017) for a complete survey of the literature.

Although there is an abundant literature that finds social norm messages are effective, there have been few studies of the long-term effect of social norm nudging. Ferraro and Price (2011) finds the effects of social norms in nudging people toward water saving persist after two years. Bernedo et al. (2014) finds the effect of a social comparison message declines by 50% after the first year. The effect is still observable after six years. Allcott and Rogers (2014) studied the short- and long-term effect of home energy reports with comparison messages sent by OPWER. They repeatedly sent home energy reports and found there was a high frequency of action and backsliding. After repeating the messages for two years, they found a persistent effect though it declined by 10% to 20% each year. However, these experiments were almost all conducted in the United States (Allcott, 2011; Allcott and Rogers, 2014; Bernedo et al., 2014; Brandon et al., 2017). One exception is Torres and Carlsson (2018), who ran a field experiment in Colombia to save water by using social information and appeals to norm-based behavior. Can social norm messages have the same effect in other developing countries such as China? To the best of our knowledge, there have been no studies of the effect of social norms on household energy consumption in China.

We ran a natural field experiment in dormitories at Xi'an Jiaotong University, China by sending social comparison messages about electricity consumption. We found that a one-time social comparison intervention did not lead to energy conservation on average. However, in the first week after the treatment, the social comparison messages reduced the energy consumption of the low-end users and the high-end users by 26% and 14%, respectively.

In addition, we found the treatment effect disappeared in the second week. This is consistent with Allcott and Rogers (2014) that only repeated social comparison messages can have a lasting change on behavior.

Similar studies have been done in student dormitories. Delmas and Lessem (2014) ran a field experiment in the residence halls at the University of California-Los Angeles. They compared the effect of private information with real-time appliance level feedback and social norm over usage with public information about conservation rating. They found the private information alone was not effective. Public information combined with private information reduced electricity consumption by 20%. Myers and Souza (2020) also ran a field experiment in a college residence by repeatedly mailing the social comparison Home Energy Reports (HERs) to dormitories. They find the reports induced almost no behavioral change among tenants. Because tenants in college dormitories do not pay the electricity bill, the authors argued that social norms may not motivate behavioral change in the absence of monetary incentives. Our experiment differs from these studies in the following aspects. Firstly, student tenants in our experiment have to buy electricity if they use more than the freely given quota; Secondly, we send the social comparison message only once and in person. Thirdly, our social comparison message is different from the HERs used in Myers and Souza (2020) and the dashboard used in Delmas and Lessem (2014).

Our paper is organized as follows. We present a theoretical model in section 2. Section 3 is the experiment design. Section 4 are the data and results. Section 5 is the robustness check. We conclude in section 6.

2 Theoretical model

Our theoretical framework is based on Levitt and List (2007). In the model, an individual's utility depends not only on wealth, but also on the decision to do the right or moral thing. An individual i's utility function can be represented as

$$U_i(a, n, s; n) = c_i(a; \theta) - M_i(a, n, s; \theta) \tag{1}$$

where U_i is the individual i's total utility; a is the individual i's consumption level; n is the perceived extent of social norms; s is the extent of the individual i's actions being scrutinized. θ is a vector of the individual's characteristics; c_i is the consumption utility; M_i is the individual i's moral cost.

In this model, the moral cost depends on the moral return related to an individual's activities. An activity that is immoral, antisocial, or conflicts with the individual's identity imposes a moral cost. The moral cost varies by individuals and societies. In practice, many factors affect the moral cost associated with an activity. For example, when an individual's action imposes an externality on others, the larger the negative externality it generates, the higher is the moral cost. In addition, the extent of the scrutiny the action is under also has impacts on the moral cost. When a consumer's utility maximization problem has a moral cost, she will deviate from the previous utility maximization problem and choose an action with a low moral cost. When an individual abides by different moral codes, she will choose different actions when facing the same decision problem(Frey et al., 1996).

We assume the consumption utility is increasing and concave in consumption a. The moral cost M depends not only on consumption a, but also on the extent to which the action is under scrutiny, and the extent of the perception of the social norm. The moral cost increases with both s and n. A utility maximizing individual faces the choice of consumption a. We assume M is increasing and convex in a. A social comparison message will increase the extent of an individual's perception of the social norm. A moral persuasion message will increase the extent of her perception that her action is under scrutiny. Both increase the moral cost of consumption. A rational individual will choose to reduce her consumption and to increase her marginal utility from consumption. When the marginal utility equals the marginal moral cost, the consumption is utility maximizing.

3 Hypothesis and experiment design

3.1 Hypothesis

We studied the effect of social comparison messages and technical advice for energy saving on consumers' energy use. We tested the following three hypotheses:

Hypothesis 1: both the social comparison messages and the technical advice for energy saving are effective in promoting energy saving behavior of consumers.

Hypothesis 2: The social comparison message is more effective than the technical advice in promoting energy saving behavior.

Hypothesis 3: The effect of a social comparison message declines with time and is heterogeneous among both high and low users of energy.

3.2 Experiment design

We had two treatment groups. We deliver an electricity use report in person at period $t = 0$ to dormitories where the individuals in treatment group 1 resided. We chose a Sunday night to deliver the treatment materials to the dormitories. Most student tenants stay in the dormitory during this period. We knocked on each dormitory and handed the materials to the residents in person. When no one was in the dormitory, we put the materials through the door with the face up. We tried to make sure student tenants would see the materials when they entered. About 80% to 90% of dormitories had a tenant inside. The report included the dormitory's electricity use in the previous week, the average electricity use among neighbors, and the relative positions of individuals in the treatment group among their neighbors (see the appendix A1 for a sample). Treatment group 2 received a moral persuasion message with technical advice on how to save electricity at period $t = 0$ (see the appendix A2 for a sample). Both treatments were administered one time and electricity use was collected once a week afterwards. We also randomly chose a control group with no treatment.

We obtained permission to conduct the study from the university's logistics department's energy service center. We obtained weekly electricity use data for three dormitory buildings. The tenants of the dormitories are female graduate students. The dormitories are standardized and each has an air-conditioner. There are no other large electrical appliances besides lighting. Each dormitory does not have to pay electricity bill if it does not reach 190 kWh/semester (one semester is about 18 weeks). The experiment took place from November 4 to December 23, 2018. We ran a pilot study before the experiment with 69 dormitories in September. We calculated the sample size with a power test[1]. We chose a sample size of 585 dormitories. We randomly divided the sample into three groups with 195 dormitories for each group. The treatment groups received the respective treatments from the beginning

[1]The results are available from the authors upon request.

of the second week. After we had collected six weeks' electricity use data, we deleted those dormitories with zero electricity use for two consecutive weeks. We also deleted dormitories that did not have precise reports of electricity use because of problems with the smart meter equipment. In total we had a sample of 575 dormitories. The experiment design is shown in table 1.

4 Data and results

4.1 Descriptive statistics

We collected the cumulative electricity use for each dormitory at the end of each week for six consecutive weeks. We obtained the usage in each week by first difference the cumulative data. The descriptive statistics of electricity use are in table 2.

Table 2 shows the mean usage was 13.14 kWh, 13.23 kWh, and 13.37 kWh for the control group, treatment group 1, and treatment group 2, respectively. The median usage was 9 kWh, 10 kWh, and 10 kWh, respectively. We used the two samples with equal variance t test and found no statistical differences in usage among the three groups in the first week. The p values for the three tests are 0.937, 0.844, and 0.902. The average use in the second week was 17.48 kWh for the control group, 17.11 kWh for treatment group 1, and 17.20 kWh for treatment group 2. The increase was driven by a large fall in the temperature in the area of the study. The average high temperature fell from 14.5 degrees Celsius to 10.5 degrees Celsius. The average low temperature fell from 4.6 degrees Celsius to 2.2 degrees Celsius. There was no heating in the dormitories and tenants increased their use of the air conditioners for heating. After the second week, the average electricity use started to decline due to the beginning of collective heating. The use of air conditioners for heating decreased.

Figure 1 shows the average electricity usage was almost the same among the three groups. In the second week, the average electricity use was lower in treatment groups 1 and 2 than in the control group. From week 4, the average electricity use gap between the control group and treatment group 2 declined and disappeared by the end of the sixth week. There is still a gap between the control group and treatment group 1. At the end of the sixth week, the average electricity use of treatment group 1 was lower than the other two groups.

4.2 Regression analysis

We used the regression model in equation 2 to analyze the data.

$$Y_{it} = \alpha + \gamma_i + \delta_i \Sigma_{j=1}^{5} week_j + \beta_1 d_{i1} T_i + \beta_2 d_{i2} T_i + \epsilon_{it} \tag{2}$$

where Y_{it} represents the electricity use at week t for the dormitory i; γ_i is an individual fixed effect variable. If γ_i is independent of all other explanatory variables, equation 2 is a random effect model. $week_j$ is a dummy variable for time. $week_j = 1$ means the first week after the treatment. $week_j = 0$ means it is not in the jth week. If $week_j = 0$ for all j, it is in the first week. T_i is a dummy for treatment. $T_i = 1$ means the dormitory i has received the treatment; otherwise it has not received the treatment. d_{i1} and d_{i2} are dummy variables for group. $d_{i1} = 1$ means the dormitory is in treatment group 1; $d_{i2} = 1$ means the dormitory is in treatment group 2. If both d_{i1} and d_{i2} equal zero, the dormitory is in the control group.

We ran regressions with ordinary least square (OLS), fixed effect, and random effect models. The results are reported in Table 3. In column (1) OLS regression, the coefficients of interaction terms $treat1 \times T$ and $treat2 \times T$

which are the treatment effects are -0.291 and -0.121. The social comparison message in treatment group 1 reduced electricity consumption by 0.291 on average. The moral persuasion and technical advice reduced electricity consumption by 0.121 on average. However, the average treatment effects were not statistically significant. In the fixed effect model shown in column (2), the average treatment effects became -0.380 and -0.346. In the random effect model shown in column (3), the average treatment effects were -0.339 and -0.244. The dummies for week are significant at the 1% significance level. The average electricity use increased after the first week and then declined. We used the Hausman test to compare the fixed effect and the random effect models. The p value is close to 1 and we failed to reject the null hypothesis that there are no differences between the estimates in the two models.

4.3 Low-end users

We categorized the lowest 25% electricity users in the first week as the low-end users. The average electricity use and the change relative to the previous week is displayed in table 4.

In the first week, the average electricity use was 4.69 kWh, 4.61 kWh, and 4.33 kWh for the control group, treatment group 1, and treatment group 2, respectively. The p values from the two-sample equal variance t test are 0.30, 0.76, and 0.19. We found no statistical differences among the three groups, which confirmed that our sample was randomly divided into the three groups. After the first week of treatment, the control group's average electricity use increased by 118%, while treatment group 1 and group 2 both increased, by 79% and 96%, respectively. Figure 2 shows the treatment effects were large in the second week and then declined. The average electricity usage among the three groups was close by the sixth week. The treatment effect did not persist. We did not see the boomerang effect that was found in previous research (Schultz et al., 2007). The average electricity use in both treatment groups decreased relative to the control group.

We used the following regression equation 3 to do the analysis and it confirmed our preliminary results.

$$Y_{it} = \alpha + \gamma_i + \delta week + \beta_1 d_{i1} \times week + \beta_2 d_{i2} \times week + \epsilon_{it} \tag{3}$$

where week is a dummy variable. The panel data we used for each regression had two periods. The first period was the first week without treatment; the second period was the average electricity use from the second week to the sixth week. For example, when we studied the sixth week's treatment effect, we used the data from the first week and the sixth week. week=0 represents the first week and week=1 is the sixth week. We also included a dummy γ_i to capture the dormitory fixed effect. We used the OLS, fixed effect, and random effect models separately. The results are reported in table 5, 6, and 7. We used the Hausman test and found the p value is close to 1. We failed to reject the null hypothesis that the estimates from both random effect and fixed effect models are equal.

Table 7 shows the estimated coefficients for the interaction terms $treat1 \times week$ and $treat2 \times week$ are -1.833 and -1.607. In the week after the treatment, the group that received the social comparison messages reduced electricity consumption by 1.833 kWh on average relative to the control group. The group that received the moral persuasion and technical advice messages reduced electricity consumption by 1.607 kWh on average relative to the control group. The average electricity use for the low-end users in the control group was 10.22 kWh in the second week. Treatment groups 1 and 2 reduced average consumption by 17.9% and 15.7% relative to the control group. In the second week after the treatment, groups 1 and 2 reduced electricity consumption by 1.456 (20.3%) and 1.545 (21.6%), respectively, relative to the control group. Although the treatment effects are not statistically significant, they are large in magnitude. The treatment effects for the low-end users were much larger than previously reported in the literature. Allcott (2011) found a 0.3% reduction for the low-end electricity users. Ferraro and Price (2011) found the social comparison messages reduced average water use of low-end users by 2.72%. In the third to fifth week after the treatment, the treatment effects were 8.43%, 5.74%, and 6.22%. The effects of the social comparison messages and moral persuasion with technical advice both declined and did not persist.

We compared the estimated coefficients in Week 2 and failed to reject the null hypothesis that $\beta_1 = \beta_2$ (p = 0.788). For week 3, we also failed to reject the null hypothesis that $\beta_1 = \beta_2$. There was no significant difference between the treatment effects of social comparison messages and the moral persuasion with technical advice.

4.4 High-end users

Users with the highest 25% of electricity use were categorized as high-end users. Their average electricity use is summarized in table 8. In the first week, the average electricity usage for the high-end users are 30.07 kWh, 28.69 kWh, and 26.59 kWh for the control group and treatment groups 1 and 2, respectively. Using the t-test with equal variance for two samples, we failed to reject the null hypothesis that there is no difference between each group's average electricity use at the 5% significance level (p values are 0.605, 0.168, and 0.374).

Table 8 shows that in the first week after the treatment, treatment group 1 increased electricity use by 1% and treatment group 2 increased electricity use by 9%. Electricity use in the control group increased by 8%. The social comparison message can reduce energy use. Figure 3 shows the average electricity use begins to converge after the second week. Thus, the treatment effect of the social comparison message declined.

We used OLS, random effect, and fixed effect models, and they confirmed our preliminary observations. The Hausman test failed to reject the null hypothesis that the estimated coefficients of the random effect and fixed effect models are the same. We report the estimations in table 9, 10, and 11. In table 11, column week 2 demonstrates the social comparison message and the moral persuasion and technical advice reduced average electricity use by 2.628 kWh and 1.179 kWh, respectively. The effects of the social comparison message and moral persuasion and technical advice were not significant. However, the social comparison messages reduced electricity use by 8.11% relative to the control group. Columns week 3 to week 6 show the effect declined with time. The moral persuasion and technical advice reduced electricity use by 3.64% relative to the control group in week 2.

5 Robustness check

We ran regressions with the full sample. We set dummies for both the low-end users and the high-end users. In addition, we used interaction terms with dummies and other independent variables. We compared the full sample results with the separate sample results. The OLS regression model is defined as equation 4.

$$Y_it = \alpha + \delta week_{it} + \beta_1 d_{i1} \times week_{it} + \beta_2 d_{i2} \times week_{it} + low + high + \delta_{L1} d_{i1} \times week_{it} \times low + \delta_{L2} d_{i2} \times week_{it} \times low + \delta_{H1} d_{i1} \times week_{it} \times high + \delta_{H2} d_{i2} \times week_{it} \times high + \epsilon_{it} \tag{4}$$

where low=1 represents the low-end users and low=0 for any other users. high=1 represents the high-end users and high=0 for any other users. δ_{L1} and δ_{L2} are the treatment effects of social comparison messages and moral persuasion with technical advice on low-end users relative to the middle users (usage at 25% to 75% level). δ_{H1} and δ_{H2} are the corresponding treatment effects on high-end users relative to the middle users. When the treatment has no effect on the middle users, δ_{L1} and δ_{L2} are the average treatment effect on low-end users. δ_{H1} and δ_{H2} are the average treatment effect on high-end users. The regression model with individual fixed effect is defined as equation 5.

$$Y_i t = \alpha + \delta week_{it} + \beta_1 d_{i1} \times week_{it} + \beta_2 d_{i2} \times week_{it} + low + high + \delta_{L1} d_{i1} \times week_{it} \times low + \delta_{L2} d_{i2} \times week_{it} \times low + \delta_{H1} d_{i1} \times week_{it} \times high + \delta_{H2} d_{i2} \times week_{it} \times high + \gamma_i + \epsilon_{it} \tag{5}$$

The regression results for the OLS, fixed effect, and random effect models are shown in table 12. Data for the first week and the second week are used in columns (1) to (3). Data for the first week and the third week are used in columns (4) to (6). Using the Hausman test, we failed to reject the null hypothesis that there are no differences in coefficient estimations between the random effect and the fixed effect model. The OLS, fixed effect, and random effect results show the low-end users reduced their electricity use by 2.680 kWh, 2.289 kWh, and 2.461 kWh relative to the control group in the first week after the treatment. The OLS and random effect results are significant at the 10% level. The average treatment effect for the moral persuasion and technical advice is not statistically significant. For the high-end users, the group that received the social comparison message reduced their electricity use by 4.656 kWh, 2.98 kWh, and 3.720 kWh, which are significant at the 10% level, in the first week after the treatment. The group that received the moral persuasion and technical advice reduced consumption by 3.400 kWh, 0.063 kWh, and 1.456 kWh, which are not significant, in the first week after the treatment.

In regressions using data for the first and the third week, the treatment effects are not significant for both the low-end users and the high- end users. The treatment effect did not persist in the second week after the treatment. This is consistent with our previous results.

In sum, in the first week after the treatment, the low-end users who received the social comparison messages reduced their consumption by 2.68 kWh relative to the control group. This is about 26% reduction relative to the control group's 10.22 kWh consumption. The high-end users who received the social comparison messages reduced their consumption by 4.656 kWh, which is about 14% reduction relative to the control group's 32.41 kWh consumption. The results are robust across models.

6 Conclusion

Social norms have been proved to be an effective way of nudging consumers toward environmentally friendly behavior. In this paper we report on a study of the persistent and heterogeneous effect of social norms on consumers' energy consumption. We found messages related to social norms reduce low-end users' electricity consumption by 26%, and high-end users' consumption by 14% in the first week after treatment. However, the effects did not persist in the second week. Our results are consistent with previous studies (Allcott, 2011). In addition, our treatment effects are larger than in previous studies. Allcott (2011) found the social norm treatment reduced consumption by households in the highest decile by 6.3%, but it only reduced consumption of households in the lowest decile by 0.3%. Our results are different from Myers and Souza (2020), who also ran the experiment with dormitories. They found the social comparison message did not lead to any behavioral change. Delmas and Lessem (2014) found private social comparison messages did not change dormitory tenants' consumption, but public information worked well. The differences may be because we ran the experiment with Chinese dormitory tenants and their experiments were conducted in the United States. In addition, we found the social norm message can also significantly reduce low-end users' consumption. There was no boomerang effect as found in Schultz et al. (2007).

Our study also has some limitations. First, we used college dormitory tenants, which are different from households. Second, our study lasted for six weeks, a shorter time span compared to other studies such as Allcott (2011) and Ferraro and Price (2011). Future research can study the effects of a combination of different tools, such as social comparison messages and moral persuasion. In addition, how to help middle-level users to conserve energy is also an area worth future study.

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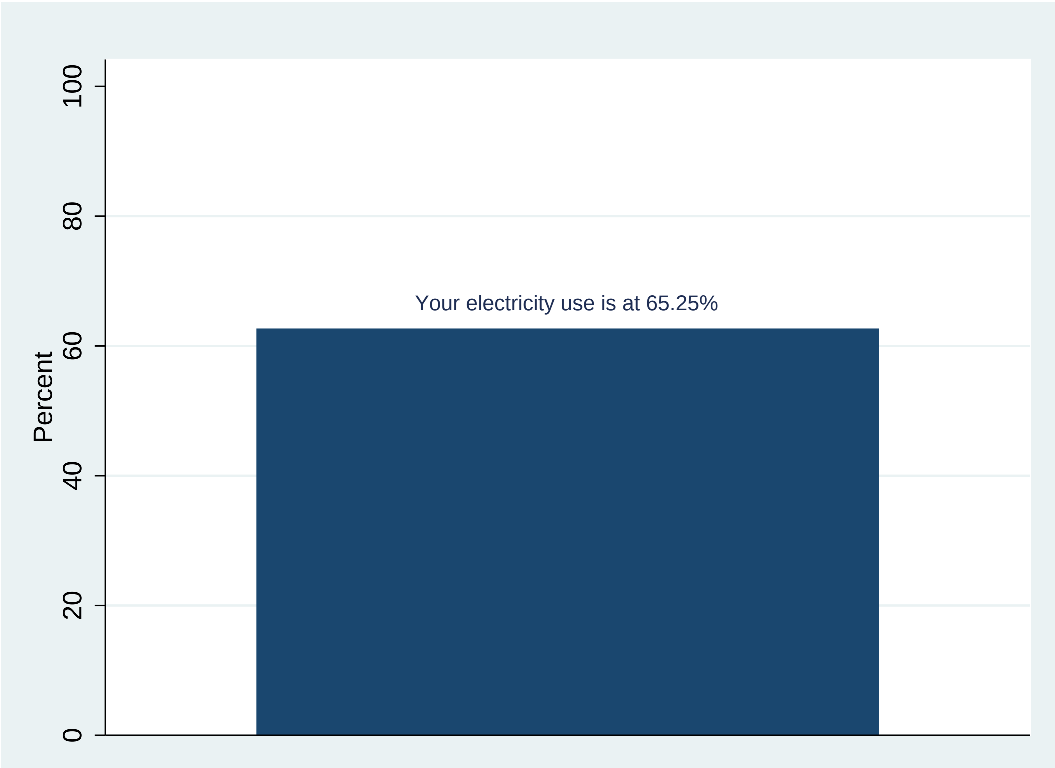
Appendix A1: Social comparison messages

Dormitory energy report

To dormitory XXX:



Your dormitory's electricity usage is 12 kWh in the past seven days. The average electricity usage in the neighborhood is 13 kWh.

Note: The figure shows the dormitory uses less electricity than 65.25% of dormitories.

Appendix A2: Moral persuasion with technical advices (translated from Chinese)

Conserve energy, Everyone has the responsibility!

With economic growth and the increase in people's living standards, electricity consumption becomes the second-highest besides water consumption. Our society is depending more and more on electricity consumption. The scientific and reasonable use of electricity has become a social problem. In the summer, there are unprecedented heatwaves, drought, and heavy precipitation in many areas of the northern hemisphere. 2018 is one of the hottest years in history. The extreme weather has great disadvantages to human health, agriculture, ecosystem, and infrastructure. The mortalities from floods and heatwaves are significantly higher than the previous years. In many cities, the extremely hot days are much more than in previous years. This is rare. Climate change is near us. The threat from an unbalanced climate is real.

The fifth assessment report by the Intergovernmental Panel on Climate Change shows human activity is the cause of global warming. If human beings cannot control greenhouse gas emissions effectively, the trend of global warming will likely continue. The risk is very high. Governments and enterprises are promoting green and low carbon development, and at the same time, millions of people are practicing a low-carbon lifestyle. This is of great help to the protection of the climate. We should start with small actions, such as dressing, dining, housing, transportation, and travelling to be greener with low carbon. For a safer and cleaner "global village", let's take actions together to protect the environment and govern our climate. Let's respect, follow, and protect nature, so we can live in harmony with our environment.

(1) Set a reasonable temperature for the air conditioner: it is better to set the temperature at 28 degrees Celsius. Setting the temperature higher by 1 degree will save 0.5 kWh for every 10 hours' running time. Using the sleeping mode can save energy by 20%.

(2) Turn off the lights as you go. According to statistics, about 10% of the residential electricity use is wasted because residents do not turn off the lights when they leave. Please remember to turn off the light as you leave. In addition, turn off electrical appliances when not in use. It will save electricity and also extend the life of the appliances.

(3) Turn off your computer and the monitor if not in use. During the break, use the computer's sleeping mode. Unplug the computer when it is turned off, otherwise, it will waste energy and reduce the computer's life. When listening to music or watching a movie, please use earphones instead of an amplifier to reduce electricity use.

(Adapted from www.people.com.cn)

Appendix B: Tables and Figures

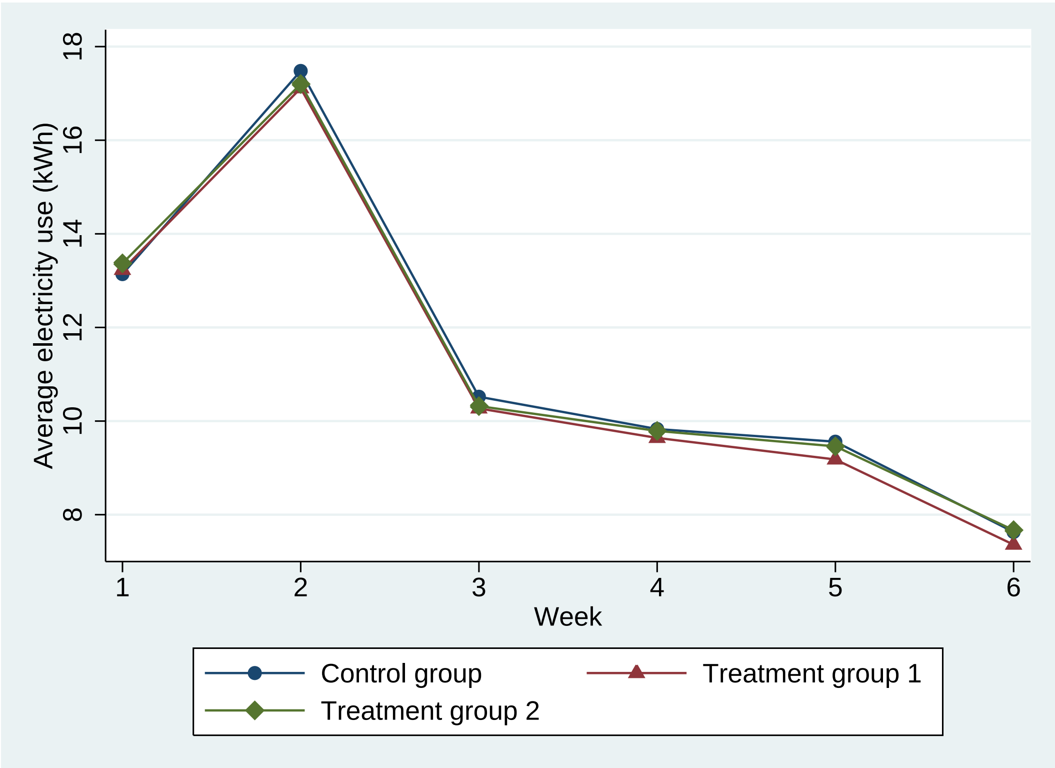


Figure 1: Average electricity use by group

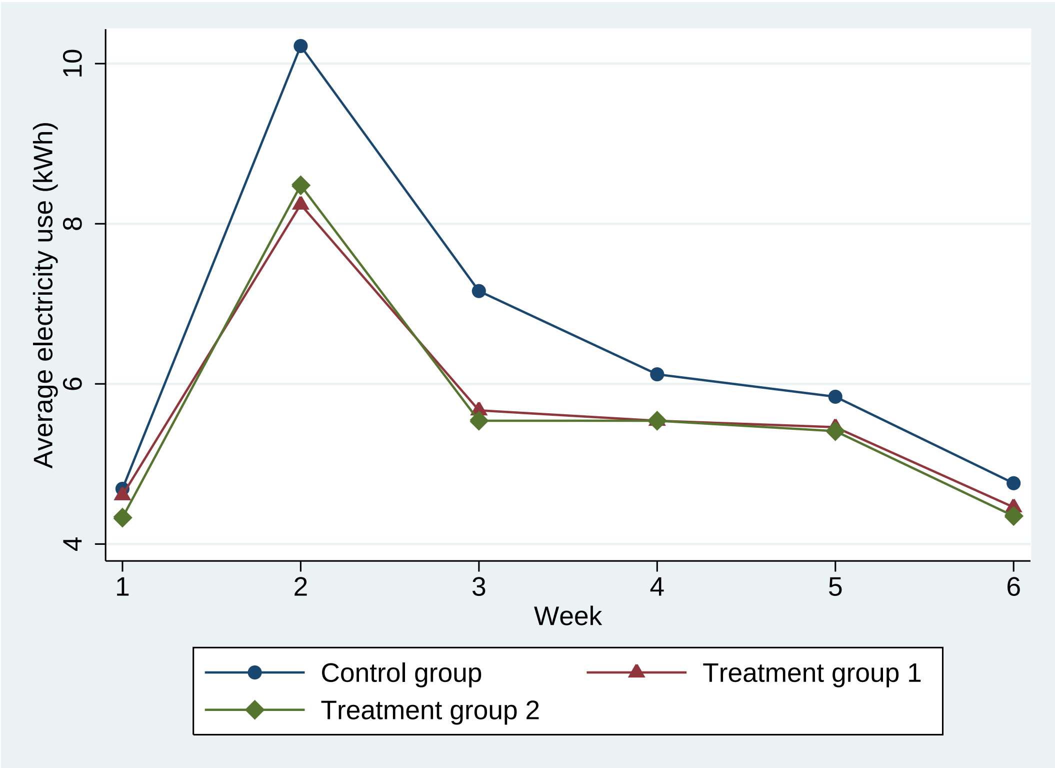


Figure 2: Average electricity use of low-end users by group

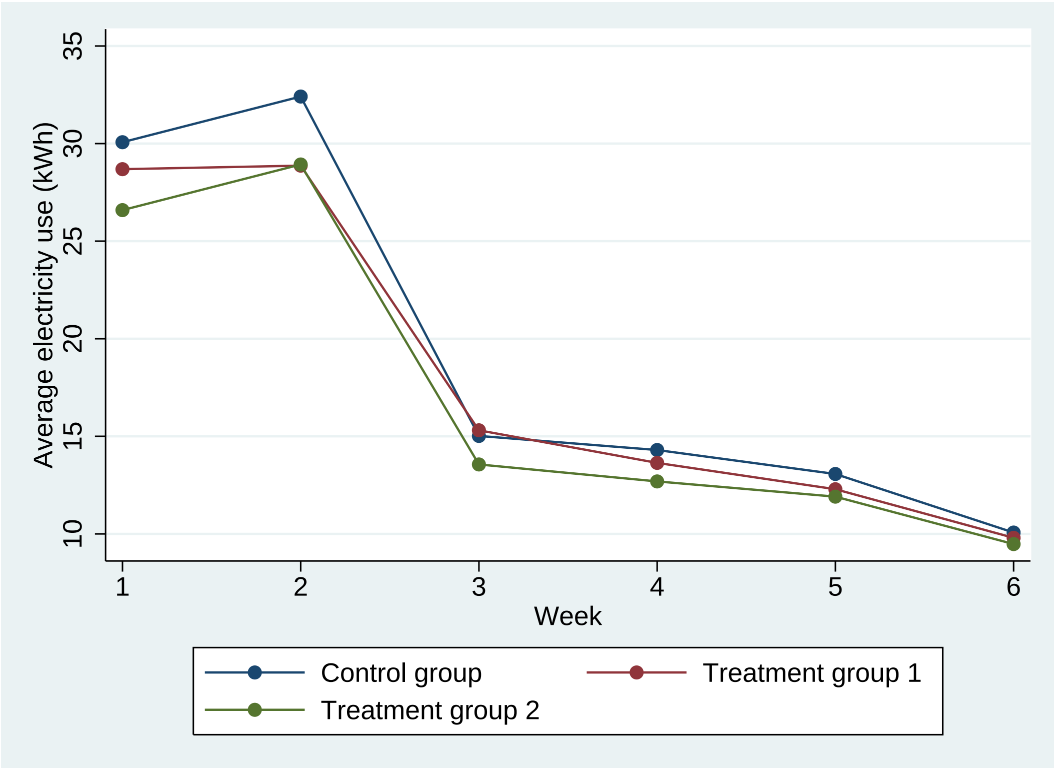


Figure 3: Average electricity use of high-end users by group

Table 1: Experiment design

Group	Size	Treatment	Starting period	Treatment time	Ending time
Control group	193	None	Week 1	None	Week 6
Treatment group 1	192	Social comparison message	Week 1	Week 2	Week 6
Treatment group 2	189	Moral persuasion with technical advices	Week 1	Week 2	Week 6

Table 2: Descriptive statistics of electricity use by groups (in kWh)

Group	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Control	13.14	17.48	10.52	9.83	9.56	7.63
n=193	9	15	9	8	8	7
	(11.54)	(11.59)	(6.73)	(6.05)	(6.68)	(5.32)
Treatment 1	13.23	17.11	10.27	9.64	9.18	7.36
n=192	10	14	8	8	8	6
	(10.73)	(11.02)	(6.57)	(5.70)	(5.22)	(4.51)
Treatment 2	13.37	17.2	10.32	9.79	9.46	7.67
n=189	10	14	9	9	8	7
	(10.78)	(11.59)	(6.09)	(5.17)	(5.58)	(4.91)

Note: for each group, the upper, middle, and lower number are the mean, median, and standard deviation value of electricity use in each week respectively.

Table 3: Panel data regression results

	OLS	FE	RE
Variables	(1)	(2)	(3)
Treat1 × T	-0.291	-0.380	-0.339
	(0.332)	(0.878)	(0.474)
Treat2 × T	-0.121	-0.346	-0.244
	(0.336)	(0.915)	(0.476)
Week1	4.156***	4.260***	4.213***
	(0.691)	(0.612)	(0.419)
Week2	-2.739***	-2.635***	-2.683***
	(0.569)	(0.700)	(0.419)
Week3	-3.353***	-3.249***	-3.296***
	(0.555)	(0.700)	(0.419)
Week4	-3.708***	-3.604***	-3.651***
	(0.562)	(0.723)	(0.419)
Week5	-5.560***	-5.456***	-5.503***
	(0.542)	(0.724)	(0.419)
Constant	13.24***	13.24***	13.24***
	(0.459)	(0.299)	(0.334)
Observations	3,444	3,444	3,444
R-squared	0.136	0.294	
Number of rooms	574	574	574

Note: Standard errors are robust; $***p < 0.01, **$
$p < 0.05, *p < 0.1$

Table 4: Electricity use of low-end users by week

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Control group	4.69	10.22	7.16	6.12	5.84	4.76
	(1.288)	(8.353)	(7.396)	(4.043)	(4.273)	(3.490)
		(118%)	(-30%)	(-15%)	(-4%)	(-18%)
Treatment group 1	4.61	8.24	5.67	5.54	5.46	4.56
	(1.201)	(3.634)	(1.967)	(1.785)	(1.963)	(2.084)
		(79%)	(-31%)	(-2%)	(-2%)	(-18%)
Treatment group 2	4.43	8.48	5.54	5.54	5.41	4.35
	(1.383)	(4.491)	(2.919)	(2.842)	(2.713)	(2.497)
		(96%)	(-35%)	(-0%)	(-2%)	(-20%)

Note: The upper number is the average electricity use. The middle number is the standard deviation. The lower number is the percent change relative to the previous week.

Table 5: OLS model for low-end users by week

Variables	Week 2	Week 3	Week 4	Week 5	Week 6
Treat1×week	-1.846	-1.468	-0.541	-0.360	-0.325
	(1.269)	(1.055)	(0.615)	(0.655)	(0.571)
Treat2×week	-1.656	-1.591	-0.553	-0.414	-0.421
	(1.323)	(1.010)	(0.694)	(0.708)	(0.602)
Week	5.589***	2.589**	1.551***	1.281**	0.224
	(1.152)	(1.019)	(0.565)	(0.595)	(0.490)
Constant	4.545***	4.545***	4.545***	4.545***	4.545***
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Observations	286	286	286	286	286
R-squared	0.2265	0.0697	0.0676	0.0470	0.0037
Number of rooms	143	143	143	143	143

Note: Standard errors are robust; $***p < 0.01, **p < 0.05, *p < 0.1$

Table 6: Fixed effect model for low-end users by week

Variables	Week 2	Week 3	Week 4	Week 5	Week 6
Treat1×week	-1.753	-1.376	-0.448	-0.268	-0.232
	(1.221)	(1.030)	(0.579)	(0.614)	(0.537)
Treat2×week	-1.290	-1.225	-0.186	-0.048	-0.055
	(1.258)	(1.065)	(0.635)	(0.655)	(0.547)
Week	5.442***	2.442**	1.404**	1.135**	0.077
	(1.106)	(0.992)	(0.540)	(0.558)	(0.450)
Constant	4.545***	4.545***	4.545***	4.545***	4.545***
	(0.237)	(0.196)	(0.117)	(0.122)	(0.106)
Observations	286	286	286	286	286
R-squared	0.226	0.069	0.066	0.045	0.001
Number of rooms	143	143	143	143	143

Note: Standard errors are robust; $***p < 0.01, **p < 0.05, *p < 0.1$

Table 7: Random effect model for low-end users by week

Variables	Week 2	Week 3	Week 4	Week 5	Week 6
Treat1×week	-1.833	-1.456	-0.513	-0.335	-0.296
	(1.262)	(1.050)	(0.594)	(0.635)	(0.549)
Treat2×week	-1.607	-1.545	-0.443	-0.314	-0.308
	(1.313)	(1.094)	(0.666)	(0.685)	(0.573)
Week	5.569***	2.571**	1.507***	1.242**	0.178
	(1.123)	(1.004)	(0.543)	(0.568)	(0.458)
Constant	4.545***	4.545***	4.545***	4.545***	4.545***
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Observations	286	286	286	286	286
R-squared	0.227	0.070	0.067	0.047	0.004
Number of rooms	143	143	143	143	143

Note: Standard errors are robust; $***p < 0.01, **p < 0.05, *p < 0.1$

Table 8: Electricity use of high-end users by week

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Control group	30.07	32.41	15.02	14.30	13.07	10.07
	(13.285)	(12.79)	(8.799)	(8.520)	(7.403)	(6.158)
		(8%)	(-54%)	(-3%)	(-9%)	(-23%)
Treatment group 1	28.69	28.87	15.31	13.64	12.29	9.80
	(11.768)	(12.369)	(9.012)	(7.649)	(7.044)	(6.126)
		(1%)	(-47%)	(-11%)	(-10%)	(-20%)
Treatment group 2	26.59	28.93	13.56	12.69	11.91	9.48
	(11.498)	(14.040)	(7.733)	(5.830)	(6.986)	(6.252)
		(9%)	(-53%)	(-6%)	(-6%)	(-20%)

Note: The upper number is the average electricity use. The middle number is the standard deviation. The lower number is the percent change relative to the previous week.

Table 9: OLS estimation for the high-end users

Variables	Week 2	Week 3	Week 4	Week 5	Week 6
Treat1×week	-3.542	0.288	-0.651	-0.779	-0.268
	(2.656)	(1.890)	(1.710)	(1.526)	(1.297)
Treat2×week	-3.483	-1.467	-1.610	-1.161	-0.587
	(2.705)	(1.687)	(1.504)	(0.461)	(1.255)
Week	4.087*	-13.29***	-14.03***	-15.25***	-18.25***
	(2.174)	(1.669)	(1.636)	(1.509)	(1.377)
Constant	28.32***	28.32***	28.32***	28.32***	28.32***
	(1.020)	(1.020)	(1.020)	(1.020)	(1.020)
Observations	286	286	286	286	286
R-squared	0.013	0.305	0.357	0.393	0.483
Number of rooms	143	143	143	143	143

Note: Standard errors are robust; $***p < 0.01, **p < 0.05, *p < 0.1$

Table 10: Fixed effect model estimation for the high-end users

Variables	Week 2	Week 3	Week 4	Week 5	Week 6
Treat1×week	-2.163	1.668	0.728	0.600	1.111
	(2.052)	(2.677)	(2.802)	(2.826)	(2.769)
Treat2×week	-0.008	2.008	1.865	2.315	2.889
	(2.215)	(2.757)	(2.777)	(2.867)	(2.835)
Week	2.341	-15.05***	-15.77***	-17.00***	-20.00***
	(1.573)	(2.137)	(2.288)	(2.276)	(2.237)
Constant	28.32***	28.32***	28.32***	28.32***	28.32***
	(0.434)	(0.530)	(0.526)	(0.548)	(0.541)
Observations	286	286	286	286	286
R-squared	0.006	0.298	0.350	0.386	0.477
Number of rooms	143	143	143	143	143

Note: Standard errors are robust; $***p < 0.01, **p < 0.05, *p < 0.1$

Table 11: Random effect model estimation for the high-end users

Variables	Week 2	Week 3	Week 4	Week 5	Week 6
Treat1×week	-2.628	0.656	-0.361	-0.598	-0.134
	(1.898)	(1.770)	(1.672)	(1.508)	(1.285)
Treat2×week	-1.179	-0.540	-0.879	-0.703	-0.248
	(2.071)	(1.692)	(1.532)	(1.485)	(1.282)
Week	2.929**	-13.76***	-14.39***	-15.48***	-18.42***
	(1.456)	(1.581)	(1.642)	(1.535)	(1.422)
Constant	28.32***	28.32***	28.32***	28.32***	28.32***
	(1.022)	(1.022)	(1.022)	(1.022)	(1.022)
Observations	286	286	286	286	286
R-squared	0.010	0.305	0.357	0.393	0.483
Number of rooms	143	143	143	143	143

Note: Standard errors are robust; $***p < 0.01, **p < 0.05, *p < 0.1$

Table 12: Whole sample regression results

Variables	1	2	3	4	5	6
Treat1×week×low	-2.680*	-2.289	-2.461*	-1.159	-0.768	-1.054
	(1.572)	(1.461)	(1.495)	(1.211)	(1.178)	(1.186)
Treat2×week×low	-1.670	-1.260	-1.440	-2.020	-1.610	-1.911
	(1.501)	(1.379)	(1.416)	(1.250)	(1.200)	(1.220)
Treat1×week×high	-4.656*	-2.98*	-3.720*	0.509	2.176	0.954
	(2.796)	(2.184)	(2.087)	(1.969)	(2.728)	(1.853)
Treat2×week×high	-3.400	0.063	-1.456	-1.925	1.538	-1.000
	(2.791)	(2.277)	(2.174)	(1.783)	(2.801)	(1.776)
Treat1×week	1.113	0.825	0.952	-0.220	-0.508	-0.297
	(0.888)	(0.770)	(0.803)	(0.596)	(0.576)	(0.567)
Treat2×week	-0.084	-0.071	-0.076	0.457	0.470	0.461
	(0.707)	(0.564)	(0.603)	(0.587)	(0.551)	(0.554)
Low	-5.531***		-5.531***	-5.531***		-5.531***
	(0.188)		(0.188)	(0.188)		(0.188)
High	18.245***		18.245***	18.25***		18.25***
	(1.030)		(1.031)	(1.030)		(1.031)
Week	4.563***	4.660***	4.617***	0.233	-0.330	0.259
	(0.474)	(0.330)	(0.353)	(0.377)	(0.335)	(0.327)
Week×low	1.046	0.783	0.898	2.318***	2.055**	2.248**
	1.243	(1.150)	(1.167)	(1.708)	(1.047)	(1.052)
Week×high	-0.475	-2.319	-1.510	-13.532***	-15.38***	-14.02***
	(2.221)	(1.601)	(1.497)	(1.708)	(2.155)	(1.610)
Constant	10.08***	13.24***	10.08***	10.08***	13.24***	10.08***
	(0.154)	(0.145)	(0.154)	(0.154)	(0.153)	(0.154)
Time	week:1,2	week:1,2	week:1,2	week:1,3	week:1,3	week:1,3
Model	OLS	FE	RE	OLS	FE	RE
Observations	1,148	1,148	1,148	1,148	1,148	1,148
R-squared	0.577	0.0004	0.576	0.563	0.019	0.562
Number of rooms	574	574	574	574	574	574

Note: Standard errors are robust; $***p < 0.01, **p < 0.05, *p < 0.1$